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Automating the Identification of Worst-case Design Scenarios

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“You are here”

- This is the last in a series of papers introducing advanced methods for design automation
 - ↙ Parametric Modeling:
 - ↙ SAE 981574, ICES, July 1998
 - ↙ Design Optimization:
 - ↙ “Nonlinear Programming Applied to Thermal and Fluid Design Optimization,” ECTC/ITHERM, May 2002.
 - ↙ Automated Correlation (“Calibration”):
 - ↙ “Nonlinear Programming Applied to Calibrating Thermal and Fluid Models to Test Data,” SEMI-THERM, March 2002.
 - ↙ Multidisciplinary Analysis and Optimization (MDO/MDA):
 - ↙ “Integrated Analysis of Thermal/Structural/Optical Systems,” and “Automated Multidisciplinary Optimization of a Space-based Telescope,” SAE 2002-01-2444 and 2002-01-2445, July 2002.
 - ↙ **Automated Worst-Case Scenario Seeking**



Worst-case Design Scenarios

- The first step in a design process is to identify the worst-case scenarios.
 - ✚ The design will be developed and tested against these scenarios: their revision often forces a design change.
 - ✚ For thermal engineers: one “hot case” and one “cold case” as a minimum
- Margins and uncertainties are stacked up
 - ✚ Conditions that can't possible happen or co-exist (e.g, BOL properties combined with EOL dissipations, or steady-state at the subsolar point or within a planetary shadow)
- In spacecraft systems, it is often not clear what stack-up or combinations yield the worst case, especially with articulating components and complex dissipations



The Problem

- Despite the criticality of the results, cost of searching for the worst case scenarios can be prohibitive
 - ✚ The number of cases grows geometrically
 - ✚ Most older software does not facilitate repeated runs nor take advantage of previous solutions
 - ✚ In complex missions, the search must be repeated many times during design development
- Approaches are informal (since no standards exist) and rarely efficient. Common approaches:
 - ✚ Full factorial (FF) search (all possible combinations of discretized uncertainties)
 - ✚ Monte Carlo (MC) search (hundreds to thousands of randomized samples: a “shotgun” approach)



New Technology

- Parametric Software
 - ↙ Repeated runs can be scripted and searches automated
 - ↙ Special effort spent minimizing recalculation costs
- Latin Hypercube (LH) Scan
 - ↙ Requires fewer samples than full factorial or Monte Carlo
- NLP (Gradient-based Optimization) Search
 - ↙ Directly seeks *the* worst case with minimum evaluations
- Hybrid LH/NLP Method
- Future: Elimination of search-then-design; the elimination of worst-case scenarios altogether

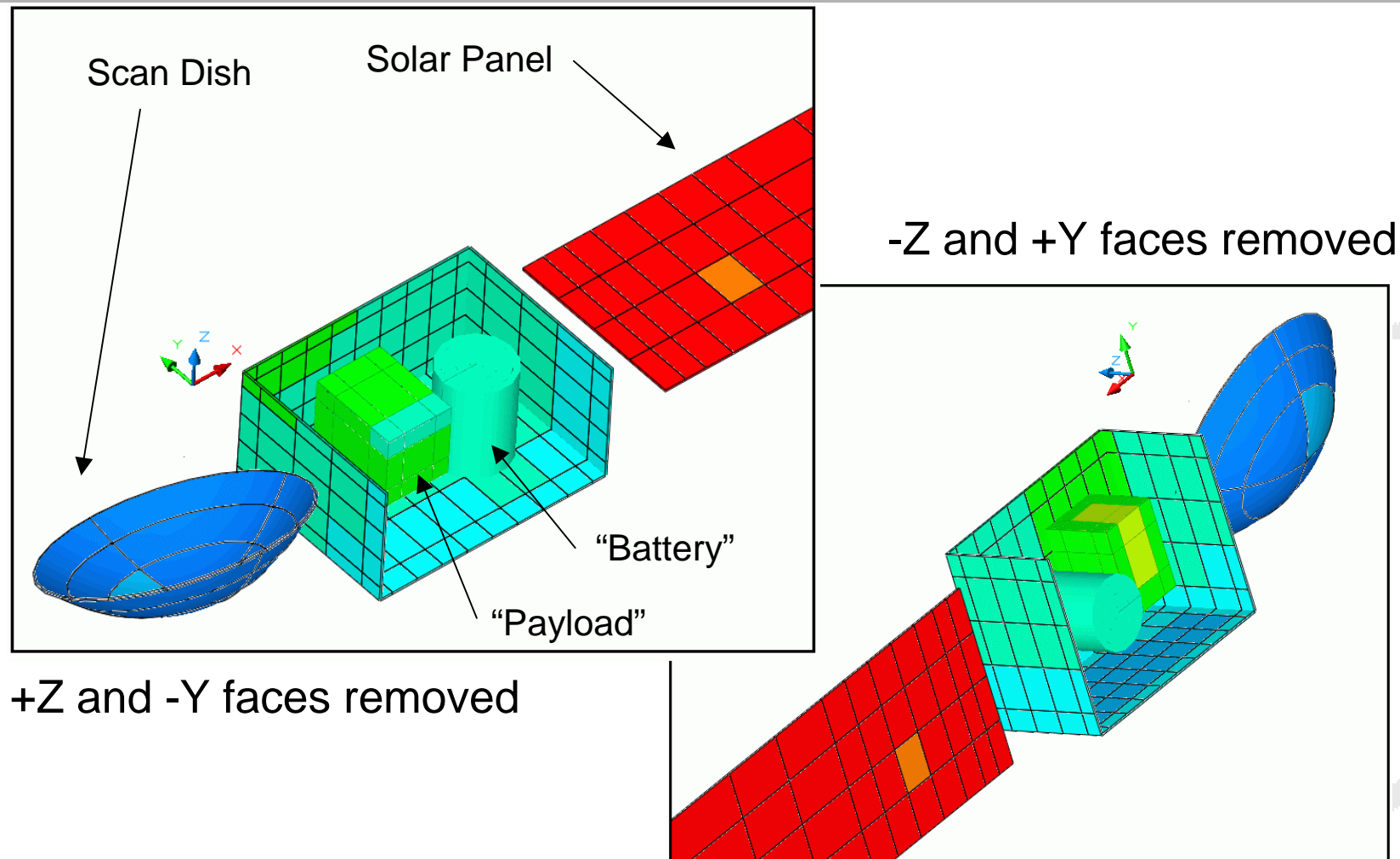


Demonstration Problem

- Simple Sample Problem:
 - ✦ 3-axis stabilized LEO (300km) nadir-facing box
 - ✦ 2-axis tracking solar panel on leading side (+X)
 - ✦ 1-axis scanning (+/- 30°) paraboloid dish on trailing side (-X)
 - ✦ 60W “payload” with 600W 10 minute pulse on the +Z face
 - ✦ SPV/CPV “battery” on the -Z face, realistic charge/discharge/trickle-charge profiles vs. shadow
 - ✦ +Y and -Y faces are fully utilized as radiators
 - ✦ Thermal Desktop® model available upon request
- What is the hot case beta angle, dish position, and start time for the power pulse?

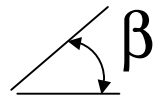
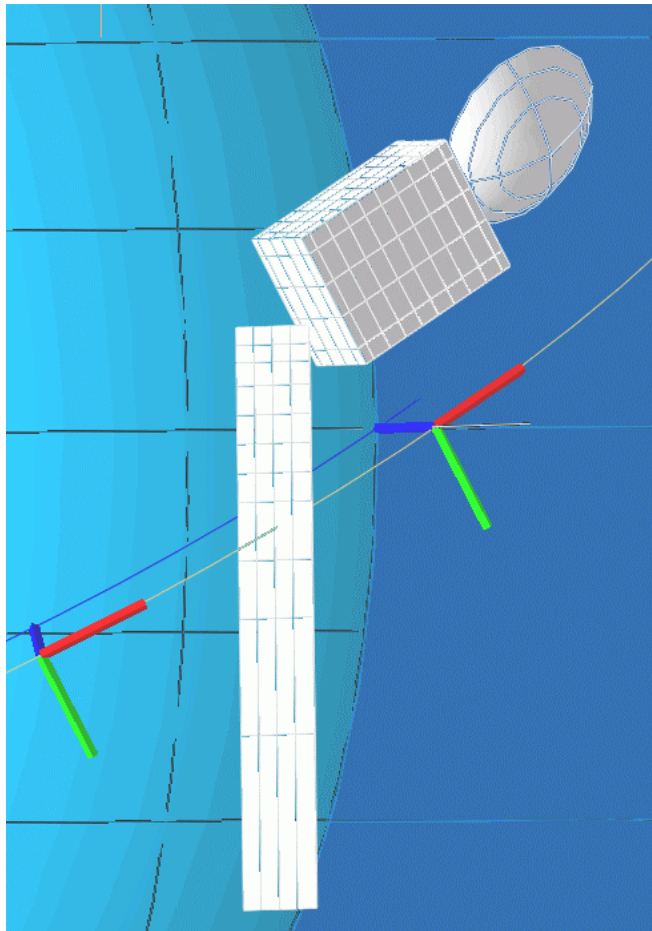


Sample Problem Definition





Sample Problem Definition



Unknowns:

1. Beta Angle (0 to 90)
2. Dish Scan Angle (-30 to 30)
3. Pulse power timing (0 to 5400s)

Shadow exit at $\beta = 30^\circ$



Tools Used

- Thermal Desktop/RadCAD® for thermal/radiation model
 - ↙ 15 orbit points, steady state plus 2 transient orbits per evaluation for cyclic convergence
- Thermal Desktop® “Dynamic Mode:” SINDA/FLUINT commands changes and recalculations as geometry/orbits change
 - ↙ per SINDA/FLUINT statistical analysis and optimization routines
- Total time to evaluate one case (all radiation and conduction recalculations, steady/transient simulations): 45 seconds on a 1.8GHz Pentium® 4.



Full Factorial Scan

(4x3x4=48 evaluations)

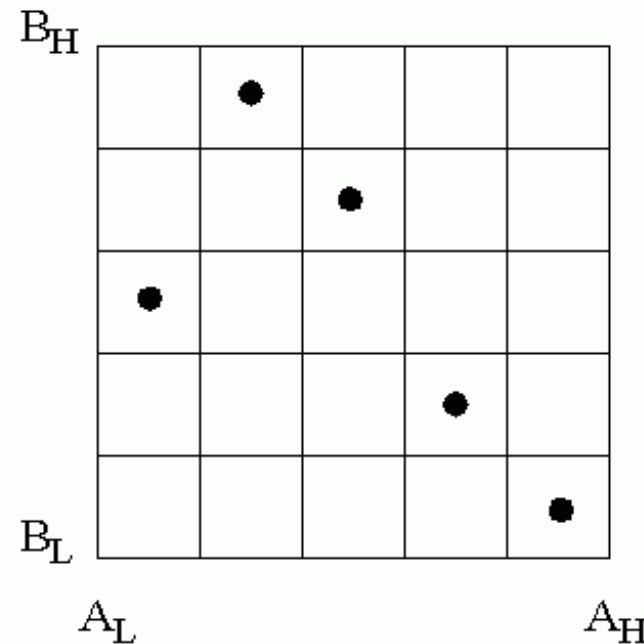
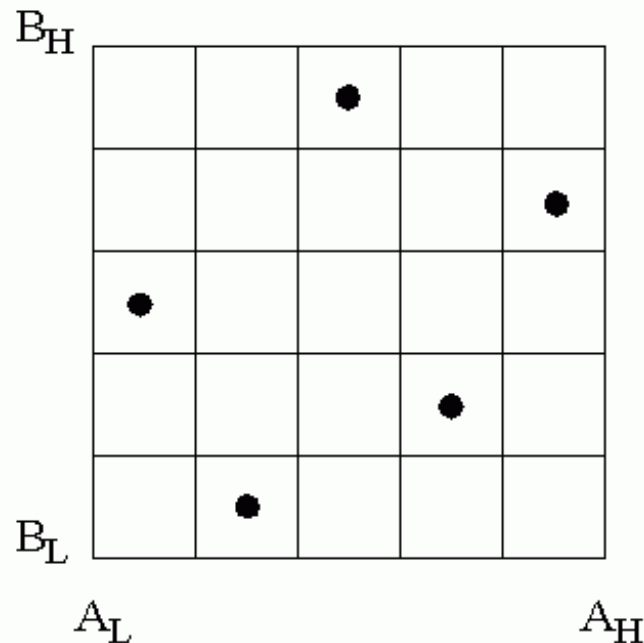
- 4 beta angles: 0, 30, 60, 90
- 3 scan angles: -30, 0, 30
- 4 pulse start times: 0, 1600, 3200, 4800 sec. from subsolar point

| Component | beta angle (deg) | scan angle (deg) | pulse start time (sec) | Peak Temp (K) | Time of Peak (sec) |
|-----------|------------------|------------------|------------------------|---------------|--------------------|
| Battery | 60 | -30 | 0 | 291.7 | 3525 |
| Payload | 90 | -30 | 0 | 301.8 | 760 |



Latin Hypercube Explained

- For N samples made, each parameter uniquely sampled $1/N$ times
- For 2 variables A and B, if $N=5$:





Latin Hypercube Results

- N=20 Samples (usually <20% of FF method)
 - ↙ Example: $\beta = 2.25, 6.75, 11.25, \dots 87.75$
- Found hotter temperatures in less evaluations:

| Component | beta angle (deg) | scan angle (deg) | pulse start time (sec) | Peak Temp (K) | Time of Peak (sec) |
|-----------|------------------|------------------|------------------------|---------------|--------------------|
| Battery | 47.25 | -1.5 | 1088 | 291.8 | 3683 |
| Payload | 78.75 | 13.5 | 122 | 303.0 | 880 |



Nonlinear Programming (Optimization) Approach

- Instead of “What is the best design” ask “What is the worst case?”
 - ✚ Best design: vary A, B, C to minimize cost
 - ✚ Worst case: what combination of A, B and C yield the maximum temperature (hot case)?
- Good news: finds the worst point, not just nearby point
- Bad news: sensitive to initial conditions
 - ✚ Number of evaluations unknown (usually 20 to 100)
 - ✚ Requires one search *per component*
 - ✚ Might ‘stall’ at a local minimum
 - ✚ This isn’t serious for design optimization, but is more troublesome for test data calibration and is *acute for worst-case seeking*



Hybrid Method

- Find good starting point with quick (say N=10) LH scan
- Finish off with NLP (optimization)
- Overcomes both initialization sensitivity of NLP and discretization limitation of LH. The cost of LH “prescan” usually pays for itself in reduced NLP evaluations

| Component | beta angle (deg) | scan angle (deg) | pulse start time (sec) | Peak Temp (K) | Time of Peak (sec) |
|-----------|------------------|------------------|------------------------|---------------|--------------------|
| Battery | 47.9 | 0.8 | 1276 | 292.1 | 3678 |
| Payload | 73.5 | 17.3 | 7.1 | 303.7 | 774 |

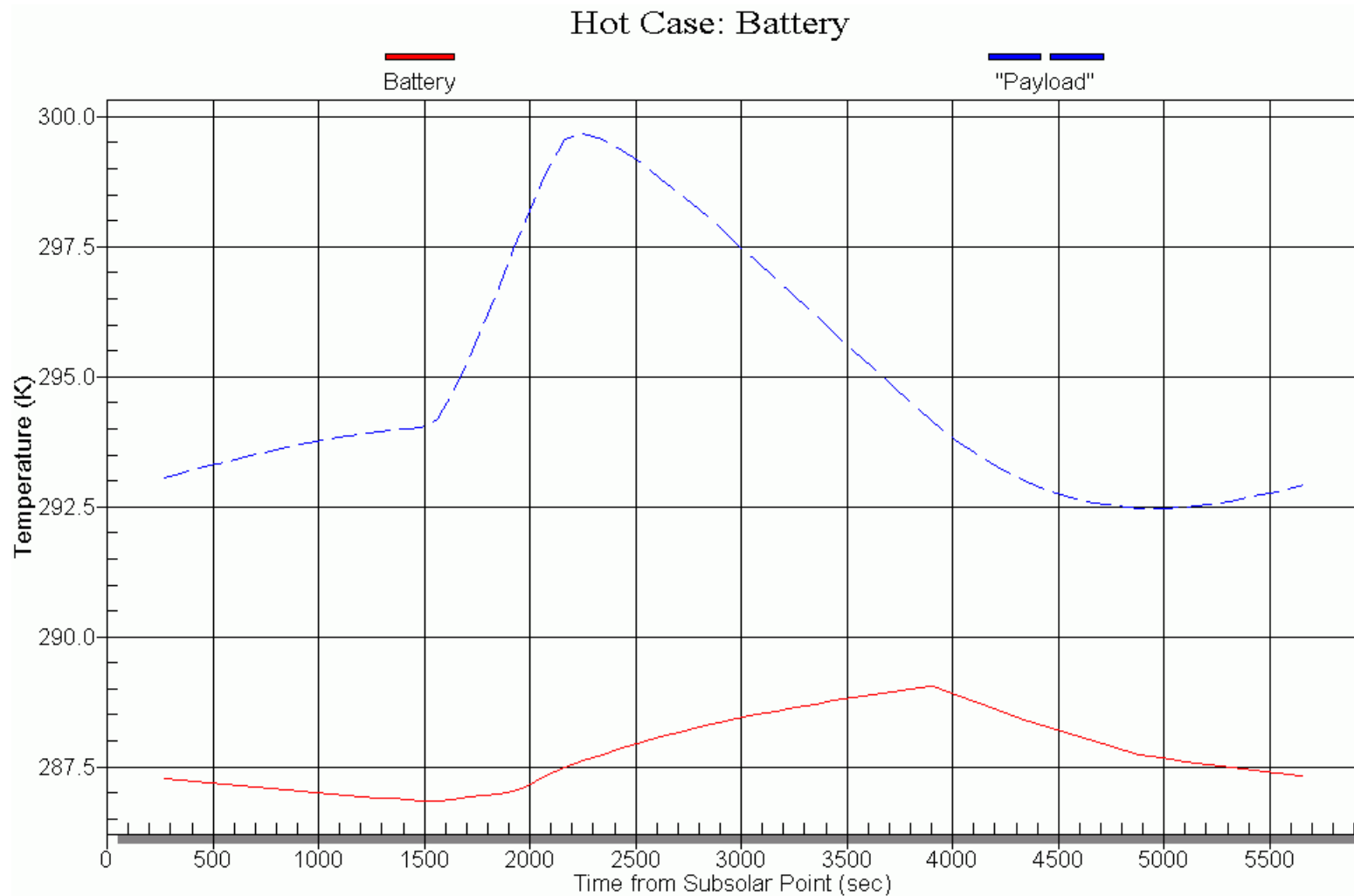


Results Discussion: Sample Model

- Results
 - ↙ Battery peaked at intermediate beta angle: too low and the -Z face doesn't get much sun, too high and the battery isn't used
 - ↙ Payload peaked at fuller sun (high beta, but less than 90!) and when pulse began near the subsolar point
- In retrospect:
 - ↙ Beta angle was the most important
 - ↙ Pulse start time was of intermediate importance
 - ↙ Scan angle for the dish was not important
- FF and MC waste time resolving unimportant parameters. Discrete sampling like LH preserves resolution of important parameters.

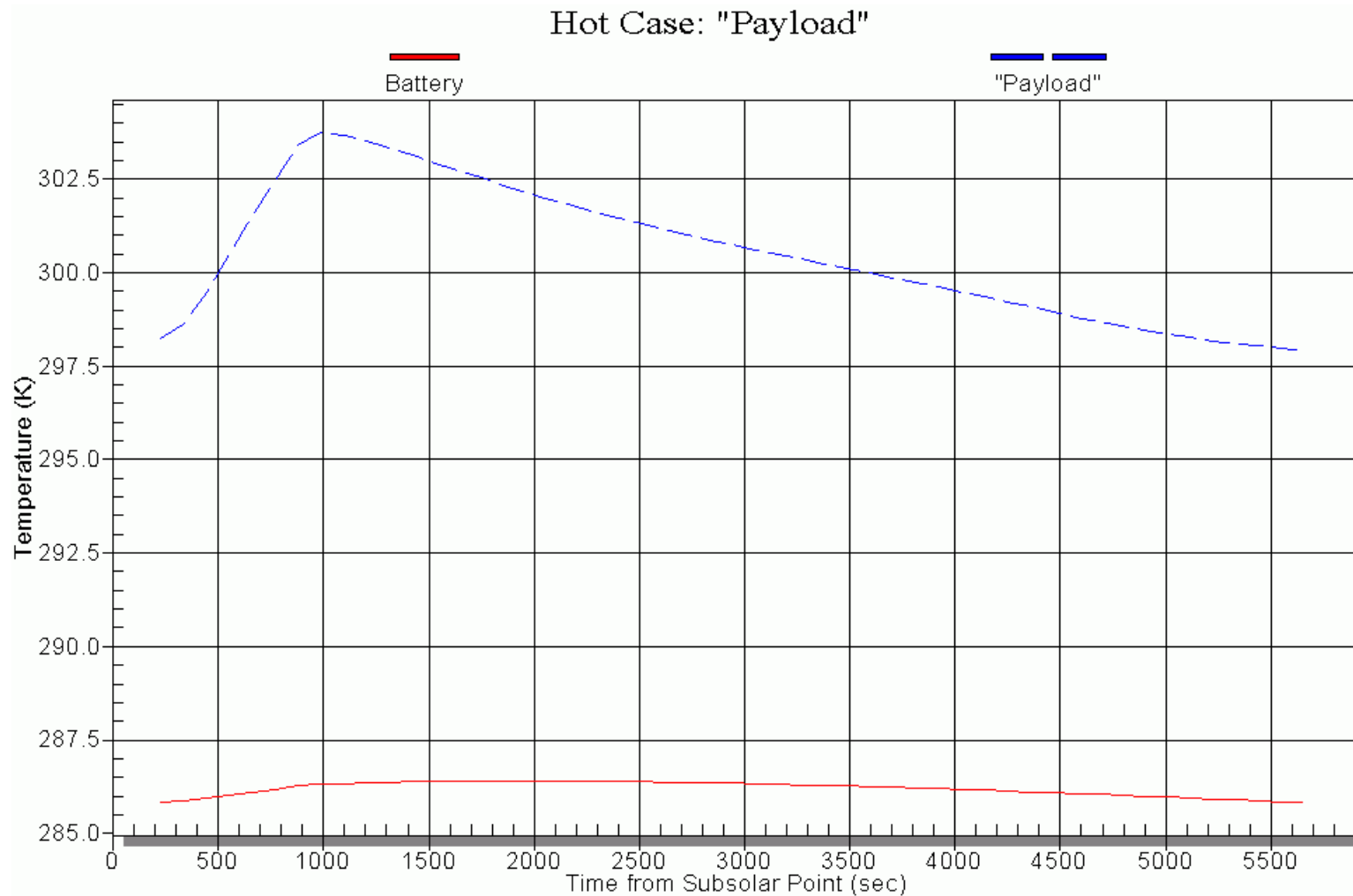


Battery's Hot Case





Payload's Hot Case





Conclusions

- Existing statistical analysis and optimization tools can significantly reduce the cost (and improve the accuracy) of worst-case searches
- Just like model calibration to test data, another nasty task has been automated



Even More Advanced Techniques

- **Near Term** (tomorrow if needed)
 - ↙ Response Surface Models (RSM)
 - ↙ Inject after the LH scan and before the NLP search to tremendously speed the latter
 - ↙ Sampling based on actual probability of occurrences rather than uniform distribution functions
 - ↙ Example: sinusoidal scan angle
- **Far Term** (the ideal, even if not currently achievable)
 - ↙ Dispense with a separate worst-case search
 - ↙ Reliability-based optimization and robust design techniques
 - ↙ Instead of a scenario-then-design-then-check, incorporate probabilistic scenarios into automated design production